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Analyzing the Dynamics of Social Vulnerability to Climate Induced Natural Disasters in Orissa, India

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Abstract

Climate induced natural disasters (CINDs) including droughts, floods, cyclones and heat waves have become serious problems to Orissa, a coastal state of India. Fluctuating weather conditions in the state suggest that it is reeling under a climatic chaos. It has been experiencing contrasting weather like heat waves to cyclone and from drought to flood for more than a decade. The dramatic change in state's ecology and weather conditions are perhaps consequences of climate change. Intergovernmental Panel on Climate Change (IPCC) links vulnerability with climatic change and point out that the vulnerability of a region depends largely on its wealth and poverty, which limits the adaptive capabilities The socio-economic systems of the state like Orissa remains more vulnerable to CIND because of high reliance on natural resources, limited ability to adapt financially and intuitionally, low per capita GDP, acute poverty and lack of safety nets. Vulnerability is social condition of measuring coping ability that differs across the regions, economic sectors and social groups. The historical disparities in the socio-economic structure of the state shaped the social vulnerability of the population and their responses to cope with looming crisis. These disparities are derived from caste, class, occupation, age difference and socially marginalized population which will result into uneven impact of hazards on the various communities in different districts of Orissa. This article examines how the pre-existing social vulnerability within different districts of Orissa interacted with catastrophe to produce socio-spatial pattern recovery. The study aims to develop composite index of social vulnerability (CISV) for the districts of Orissa by using a combination of statistical and spatial approach to improve the ability of poor people to be more resilient to current natural hazards as well as to the risks associated with long-term climate induced natural disasters. The methodology proposed in developing CISV is to overcome the persistent dichotomy in different vulnerability research and also to highlight the priority areas of policy implications in building adaptive capacity of the most vulnerable districts.

Keywords: Climate induced natural disasters (CIND), composite Index of social vulnerability (CISV), principal component analysis (PCA), human development index (HDI), Orissa, India

Twenty first century is marked by series of devastating climatic events and topics of vulnerability on public, political and scientific agenda. The most adverse impacts of climate change have been faced by socially marginalized sections of the society whose livelihoods depend upon the natural resources. The most vulnerable populations of climate change are rural communities armed with limited capabilities and opportunities to cope with extreme events like tropical cyclone, sea level rise, flood and drought (IPCC, 2007). Such sections of societies are least benefitted from fruits of modernization and industrialization and have also contributed a little to carbon foot print. Scientific evidence exists that global temperature is likely to rise 3°C or 4°C within this century and adaptation process would be difficult and complex (Parry, *et.al*, 2009; Smith, *et al.*, 2011; New, *et al.*, 2011). The scale of variability in fragile ecosystem and its adverse impacts may narrow down the window of opportunity for adaptation more than it is imagined (Adger and Barnett, 2009). Hence the challenges of climate change build over regional disparities marred by gross inequalities derived from existing socioeconomic structure and consistent failure to eradicate poverty. The socio-economic stratification and their regional distribution in a state with fragile ecosystem will certainly influence the long term adaptation and mitigation strategies.

The state of Orissa is located on the eastern coast of India and is periodically experiencing losses of life and severe damage of physical resources from tropical cyclones, floods and droughts (Dube *et al.*, 1994, 1997, 2000a, b; Das *et al.*, 1983). In the last 100 years, the state witnessed disasters for 90 years; floods have occurred for 49 years, droughts for 30 and cyclones had hit the state for 11 years. Since 1965, calamities are becoming more frequent, and striking the areas that had never experienced such phenomena. In the last 10 years, calamities have claimed more that 30,000 lives mostly in the coastal belt (Infochange, 2001). A deadly cocktail of floods, cyclones and droughts have made Orissa the disaster capital of India. Agricultural land has turned into fallow land which in turn has led to widespread malnutrition and even starvation in certain parts of the state. Further this state is a classic case of failure of trickle down economy i.e. the benefits of economic growth in Orissa has hardly brought any improvement in social condition of the people. This is one of the poorest states in India where more than two third of the population is below poverty line. Poverty has made the vulnerable segments of the population yet more vulnerable to the consequences of CINDs, especially for those living in high risk coastal areas and hilly western and southern parts of Orissa. Intraregional disparity also exists among northern, southern and eastern, western districts of the state. The poverty rate among tribal population in southern and northern part of state is 85.5% and 79.1% respectively and they mostly dependent on agriculture and forest produce for their livelihood (Census, 2001). CINDs have become a burden for the poor people of Orissa that leads to serious fiscal imbalances by heavy demands on revenue expenditure for restoring assets. There is a significant reduction of revenue in terms of taxes and duties due to the crop and property losses.

CINDs turning into severe disasters are mediated by the social vulnerability entwined into a complex interrelationship of social, economic, political, technological and institutional factors that render an exposure unit vulnerable or resilient in the face of extreme events. There are many historical and socio-demographic disparities in state of Orissa around the nexuses of caste, class, gender and age which have led social catastrophe in Super cyclone, 1999. Understanding as to how different communities will respond and adapt to these changes is thus a key element of research and policy relating to global environmental change (Vincent, 2004). All individuals or social groups exposed to hazard are not equally vulnerable rather affected people show a pattern of differential loss (Wu *et al.,* 2002). Vulnerability is social conditions of measuring the coping ability and also a combination of social resistance i.e. ability to absorb the damaging impacts of hazard and continue functions, and resilience i.e. the ability to recover from the loss quickly (Dow, 1992; Blaikie *et al.,* 1994; Cutter, 1996; Hewitt, 1997; Clark *et al.,* 1998; Wu *et al.,* 2002). The aim of the article is to map these social disparities affecting the geography of vulnerability and to develop a methodology for establishing Composite Index of Social Vulnerability to CIND. The framework of methodology relies upon the structural functionalist paradigm using social systems and regional systems as units of analysis. For the present study, districts of Orissa have been considered as units of analysis. The challenges for development are considerable as the impacts are complex and highly uncertain.

STUDY AREA

The maritime state of Orissa is situated in the northeastern part of Indian peninsula, extending from 17°.49' N to 22°.34' N latitude and from 81°.29' E to 87°.29' E longitude. The State may be broadly divided into four geographical regions as northern plateau, central river basin, eastern hills and coastal plains. The whole state lies in the tropical zone and is divided into four distinct tracts, viz. the northern plateau, the Eastern Ghats, the central tract and the coastal plains. The state is drained by three great rivers, the Mahanadi, the Brahmani and the Baitarani and some lesser rivers, all of which flow into the Bay of Bengal. The bountiful coastal area encompasses the unique Chilika lagoon (Asia's largest brackish water lagoons), Bhitrarkanika (India's second largest mangrove forest) one of richest and diverse mangrove ecosystems endowed with largest rookery of Olive Ridely (beach at Garirmata).

Further, the state is also known as disaster capital of India because the state affected by flood for 49 years, drought for 39 years and cyclone for 11 years (Down to Earth, 2001). It has highlighted that intensity and frequency of calamities are having increasing trend in last century. The state's economy is characterized by underdevelopment, poverty and unemployment. Climatic variability in Orissa during the last three decades has shown deviations in rainfall of 20% or more every third year. Promoting social and economic equity is key to successful long-term strategies to reduce people's vulnerability

to disasters. A holistic approach to disaster risk reduction, integrated with vulnerability reduction in all spheres physical, economic, social and political - is imperative.

Table 1: Increasing incidence of natural calamities in Orissa

Drought		***Flood***		***Cyclone***	***Hailstorm, Whirlwind, Tornado***	***Whirlwind, Tornado***
1965	1984	1967	**1980**	1967	1978	**1981**
1966	**1987**	1968	1981	1968		
1972	1992	1969	**1982**	**1971**		
1974	1996	1970	1985	1982		
1976	1998	1971	1990	**1999**		
1979	**2000**	1972	1992			
1980	**2002**	1973	1994			
1981		1974	1995			
1982		**1975**	**2001**			
		1977				

Note: Bold letter represents severe incidence of drought/flood/cyclone during that year; Italic letter represents the occurrence of more than one natural calamity during that year. Underlined letter represents deviations in rainfall of 20% or more than the normal (**Source:** Selvarajan *et al.,* 2002). Also refer Appendix II for more details.

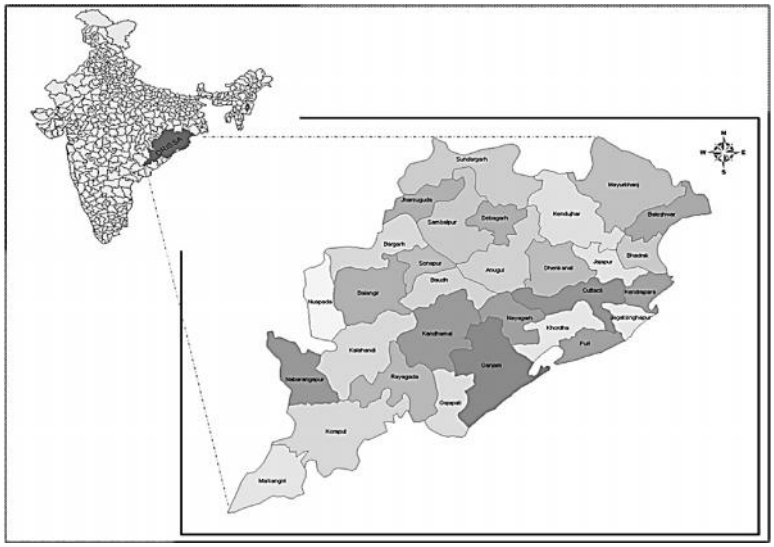

Fig. 1: Location of study area

SOCIAL VULNERABILITY INDICATORS

The impacts of climate change suggest that several demographic attributes, social and economic well being factors are important indicators of climate induced vulnerability. Some of the repeated indicators are used for analysis for social vulnerability in developing countries, although expert advice and literature are used for choosing different proxies for each indicator. Eight indicators including dependant population (DP), percent of rural population (PRP), socially dependant population (SDP), special need population (SNP), percent of illiterate population (PILP), percent of population dependent on natural resources (PPSDEN), percent of marginal workers (PMW) and human health (HH) have been considered for constructing composite index of social vulnerability.

Poverty is the most apparent indicator to show vulnerability in the space. Populations below poverty line are more vulnerable to any kind of disaster because they have less saving to spend preventative measures, emergency supplies, and recovery efforts (Blaikie *et al.,* 1994, Clark *et al.* 1998, Dhanani and Islam, 2002 and Fothergill and Peek, 2004). It shows economic condition of the people in term of size of operational landholding, type of house they posses, availability of clothes, food security, sanitation, ownership of consumer durables, literacy status, status of household labour force, means of livelihood, school enrollment of children, type of indebtedness, reason for migration from household and preference for assistance. CIND will compound existing acute and persistent poverty (47.15% of population is Below Poverty Line, Department of Panchayati Raj, Government of Orissa 1999) of the state which further reduces their accesses to drinking water, negatively affecting their health and poses a threat to food security where livelihood choices are limited.

Hence it is an important indicator to measure the ability to cope with CIND. The two demographic groups i.e. children and elders (dependant opoulation) are more susceptible to climate induced natural disasters. Both these group of population are unable bounce back on their own after disaster (Clark *et al.* 1998, Cutter *et al.,* 2000; O'Brien and Mileti, 1992; Hewitt, 1997; Ngo, 2001). In general population with a low dependency ratio (high proportion of working age adults) and in good health are likely to have the widest coping ranges and thus be least vulnerable in the face of climate change exposure. The underdevelopment status of Orissa, which by definition has high birth rates and declining death rates would result into expanding population and high dependency ratio formed largely out of under 15 age groups rather than over 65 age groups.

The extreme events induced by CIND may create significant disturbances and immediate threats to natural resources of state in 21st century. People depending upon natural resources are more vulnerable to any kind of disasters (Adger, 2000a). Orissa has more climate sensitive economy than any other state in the country because more than two-third of population depend upon natural resources for their livelihoods. The

immediate impact of CIND is change in water availability which may increase baseline vulnerability because high percentage of population in the state belongs to natural resource dependant livelihood category such as primary industries including agriculture, fishing and forestry. Productivity in these occupations is function of water availability. This is a potent indicator to measure social vulnerability to ongoing environmental changes in the state. Rural households of Orissa tend to rely mainly on climate-sensitive resources such as local water supply and agricultural land, climate-sensitive activities such as arable farming and livestock husbandry, and natural resources such as fuel wood and wild herbs. CIND will reduce the availability of local resources, limiting the option of rural household and compelling them to migrate to urban area as an alternative strategy. This can be an indicator for assessing lack of resilience and also have narrow range for villagers to cope CIND in Orissa.

Discrimination on basis of caste, class, color and religion plays major increasing vulnerability of the marginal section of the society (Pulido, 2000; Peacock *et al.,* 1997 and 2000; Bolin and Stanford, 1998; Bolin, 1993). These demographic variables play important role in quick assessment of households' potential to recover **(**Bolin and Bolton, 1986; Morrow, 1999; Enarson and Scanlon, 1999). The social vulnerability is driven by structure of family, social cohesiveness among the community, social capital and social networking (Blaikie *et al.,* 1994; Morrow, 1999). About 23 per cent of the population comprises the indigenous tribal population, mostly concentrated in the north-western and south-western districts of the state with traditional means of livelihood. The processes of modernization and CINDs have largely marginalized both these groups in economic terms, threatening their livelihood security. Hence it is a suitable indicator for understanding the dynamics of social vulnerability. The marginal workers are defined as the percentage of landless laborers in agricultural workforce, provides an indication of inequality in landholdings. Landless laborers are generally poor and have little security of income; in times of agricultural distress, laborers are the first to lose their income due to CIND. The states of Orissa has largest share of landless agricultural laborers in the country and are thus more vulnerable to shocks generated by CIND because of social and economic disruption as a result of droughts, floods, cyclone or other climatic stresses. Health is an important determinant of well-being.

Improved health is desirable as it leads to enhanced capability to work and improves adaptive capacity in climate change scenario. Improved health and nutritional status contribute to increased life expectancy. The state of Orissa is one of the malaria prone regions in India. A little more than one one-fifth death in Orissa is caused by Infectious and parasitic diseases. Hence number of people affected by different diseases is taken as indicator to measure status of heath in the state to cope with CINDs. Education is the principal attribute for assessing quality of life and plays an important role in linking social and economic development. Increased literacy level reduces vulnerability by increasing people's capabilities and access to information, thus their ability to cope

with adversities (Cutter, 1996). More the percentage of non-literates the more will be vulnerability to CIND because of lack of awareness on global changes affecting climate of the state.

DATABASE AND METHODOLOGY

Table 2.

Name of Indictors	Source of Data
Dependent Populations	Census of India (2001)
Natural Resource Dependant Populations	Directorate of Economics and Statistics, Bhubaneshwar, Orissa (2002)
Household below Poverty Line (BPL)	Department of Panchayat Raj, Government of Orissa (1999)
% of population affected by diseases	Director of Health Services, Bhubaneswar, Orissa (2002)
Marginal Workers	Census of India (2001)
Socially Dependent Population (SC+ST)	Directorate of Economics and Statistics, Bhubaneshwar, Orissa (2002)
Illiteracy	Census of India (2001)
Percentage of Rural Populations	Directorate of Economics and Statistics, Bhubaneshwar, Orissa (2002)

A wide variety of multivariate statistical techniques are available to derive a composite index from set of indicators. The choice of most appropriate method depends upon the type of problem, nature of data and objective of the analysis. In vulnerability science, indicators are generally correlated and researchers are not in a position to study the dynamics of social vulnerability with set of independent variables. It has been criticized by researchers in constructing composite index using method like ranking and indexing because of its arbitrariness and allocation of equal weights (Kundu and Raza, 1982; Dandekar Committee, 1984; Sarkar, 1985). Hence one has to look into alternative dimension reduction technique which would enable to summarize the whole set of information into a manageable form without much loss of information content of the original data. The algorithm used in this study to construct social vulnerability index broadly follows that used by Cutter *et al.* (2003), Schmidtlein *et al.* (2008) with inclusion of data standardization of input variable, weighting the selected variables and final aggregated index scores. The computations are carried out using following steps.

(I) Standardize all input variables to z-scores, by dividing each by their respective mean. This method unlike the other approaches of scale transformation (ranking, standardization, normalization and division by standard deviation) does not lead to shift in origin of the indicators in a given space.

(II) Weighting the selected variable using Principal Component Analysis). In principal component analysis (PCA), a set of original variables are transformed to a set of uncorrelated variables called principal components. The new variables are linear function

of original variables and derived in decreasing order of importance. The objective is to find the principal components which account the most variation in the original data set.

The formula to compute scores on first component extracted in principal component analysis (Stevens, 1986):

$$P_1 = b_{11}(X_1) + b_{12}(X_2) + \ldots b_1p\ (Xp)$$

Where, P_1 = the subject's score on principal component 1 (the first component extracted)

b_1p = the regression coefficient (or weight) for observed variable p, as used increasing principal component 1

Xp = the subject's score on observed variable p

In this article weighting sum of principal component analysis are used because each successive component contributes progressively less to the explainable variation. The Eigen vector corresponding to largest Eigen value of the projection matrix gives the required weight to the indicators. For analysis, only eigen value greater than one are used for weighted scores and loading value below 0.30 are suppressed (Nardo *et al.*, 2005 and Bernard, 2006). The first component is the linear combination of selected variable explaining maximum variation among the original variable and second component explain remaning variation and so on. Based on result after performing principal component analysis using SPSS software of 8 selected variable, two parsimonious components expanding explained 64% variance and 25% variance are selected for weighted sum for all districts of Odisha. The weights of the indicators are given in Table 3.

Table 3: Weight assigned to indicators by Principal Component Analysis

Indicators	PCA – 1	PCA – 2
Dependent Populations	0.708	0.543
Percentage of Rural Populations	0.558	0.768
Socially Dependent Population	0.772	-0.488
Specially Need Populations(BPL)	0.805	-0.037
Illiteracy	0.889	-0.157
Natural Resource Dependant Populations	0.844	0.472
Marginal Workers	0.858	-0.079
% of population affected by diseases	0.65	-0.585
% of Variation	**64%**	**25%**

(III) Final step is to aggregate these indicators to composite index of social vulnerability and also addressing the methodological concerns. There is a difference between aggregate indices (measure of scalar function) and composite indices (presenting a matrix of component indicators). In this paper, both the combined

approaches are used to create a single aggregate overall score, with weight derived from principal component analysis. The SOVI value will therefore be a number between 1 and 0, with 1 representing the highest level of vulnerability. The overall formula to calculate SOVI is follows:

$$SOVI = \Sigma (Ii*Wi)(Iii*Wii)(Iiii*Wiii)(Iiv*Wiv)(Iv*Wv)(I_{Vi}*Wvi)(Ivii*Wvii)(Iviii*Wviii)$$

Where I (i – viii) = Selected indicator (8)

W (i – viii) = Weighted Sum derived from PCA

THE GEOGRAPHY OF SOCIAL VULNERABILITY

The weights are multiplied to the standardize indicators and then placed in an additive model to produce the composite index of social vulnerability score for each districts and ranked according to hierarchy of their score as shown in Table-3. The CISV is a relative measure of overall social vulnerability for each district of Orissa. More than half (60%) of districts of Orissa exhibit moderate to least vulnerable levels of social vulnerability and 40% having high to extreme vulnerability. The CISV ranges from 0.443 (low social vulnerability) to 1.107 (high social vulnerability) with mean vulnerability score of 0.760 (SD + 0.184) for all the districts in Orissa. The coping ability of 16 districts are less than state average (0.741) to resist or handle climate induced natural hazards in Orissa.

Please put some methodlogy to classify the score into high, medimum, low and least vulnerable and show in it in graphs like spider diagram, any other graphs

The most vulnerable districts in Orissa to CIND

Table 4.

District	CISV-Score	Rank
Nabrangapur	0.993	5
Rayagada	1.009	4
Khandhamal	1.079	3
Nuapara	1.099	2
Malkanigiri	1.107	1

The most vulnerable districts due to CIND are Malakangiri (1.107) followed by Nuapara (1.099), Kandhamal (1.079), Rayagada (1.009) and Nabrangpur (0.993). These districts have less potential to cope with extreme climatic events. These districts are

most vulnerable to climatic variability due to high percentage of dependent population, high reliance on natural resources, limited ability to adapt financially and institutionally, low per capita GDP and high poverty, and a lack of safety nets. In particular, the district of Malkangiri with steep Ghats, plateaus and valleys sparsely inhabited by primitive tribes like Bondas, Koyas, Porjas and Didiyas was found to be most vulnerable district because of high percentage of socially dependant population (78.32%), high rate of illiteracy (68.74%), prevalence of acute poverty and also majority (91.3%) of the population's livelihood depend upon natural resources.

It is also one of the malaria prone areas of Orissa. Malkangiri is one of the most backward districts of Orissa and deserves a special attention and proper planning to enhance the capability to cope with upcoming climatic shocks. The tribal hilly district of Nuapada is second most vulnerable district because of 85% of families live below poverty line high percentage of dependant population (24.69%), majority of the population depend upon natural resources for their livelihood and 46.12% belong to marginal workers having no agricultural land. This is one of the poorest district of Orissa where 50% of families are 'very poor' with an income of only Rs.6000 (US$120) per annum (Ministry of Rural Development BPL survey, 2002). Kandhamal district, in the heart of Orissa, is God's own country — an area of great natural beauty, dotted with springs, waterfalls, lush forests and green hills back in headline as symbol of religious strife ranked third most vulnerable districts to CIND.

Almost 66% of the land area of the district is covered with dense forest and towering mountains which provide shelter to more than half (52%) of population of aboriginal people like Khandas classified under the ancient Gondid race of Proto-Austroloid group have high dependency ratio (24.13%), whereas more than two-third population depend solely on forest produce and is also one of the malaria prone region of Orissa. Almost 78.48% of population lives below poverty line which further reduce their ability to cope with natural hazards. The artificially created social and religious divide will further reduce their ability to cope because thousands have been rendered homeless and without hope or sustenance.

The district of Rayagada has been the homeland of various tribal communities with their sub-tribes rank 4th position in the ladder, owing to bad performance exhibited by attributes such as majority of population (70.32%) belong to marginalized section of society having very low literacy level (35.61%), health status is very poor and also depend upon pre-agricultural economy based on foraging, hunting and gathering but they now primarily depend on a subsistence agriculture i.e. shifting cultivation or slash and burn cultivation or *Podu* are the factors playing role in creating inability of the district to cope with climatic stresses in Orissa. District of Nabrangpur mostly has tribal, nomadic and aboriginal population ranked 5th position in list of most vulnerable districts to natural hazard in Orissa. This district has high dependant population, high degree of poverty, widespread non-literacy and more dependence on agriculture and

forest produce for their livelihood are the contributing factors for least ability to counter natural hazards in Orissa.

Table 5: Composite Index of Social Vulnerability and Human Development Index for districts of Orissa

Districts	CISV	Rank	District	HDI	Rank
Khurda	0.443	30	Khurdha	0.736	1
Puri	0.520	29	Jharsuguda	0.722	2
Jagatsinghpur	0.525	28	Cuttack	0.695	3
Kendrapa	0.557	27	Sundargarh	0.683	4
Bhadrak	0.564	26	Debagarh	0.669	5
Cuttack	0.581	25	Anugul	0.663	6
Jajpur	0.586	24	Puri	0.657	7
Nayagarh	0.600	23	Bhadrak	0.646	8
Balasore	0.614	22	Mayurbhanj	0.639	9
Ganjam	0.645	21	Kendrapara	0.626	10
Angul	0.652	20	Kalahandi	0.606	11
Jharsiguda	0.656	19	Dhenkanal	0.591	12
Baragarh	0.678	18	Sambalpur	0.589	13
Dhenkanal	0.684	17	Nuapada	0.581	14
Orissa	0.741		Orissa	0.579	
Sonepur	0.743	16	Nayagarh	0.571	15
Boudh	0.770	15	Sonapur	0.566	16
Bolagiri	0.772	14	Bargarh	0.565	17
Sambalpur	0.778	13	Baleshwar	0.559	18
Keonjhar	0.820	12	Jagatsinghpur	0.557	19
Kalahandi	0.852	11	Ganjam	0.551	20
Mayurbhanj	0.859	10	Balangir	0.546	21
Deogarh	0.891	9	Jajapur	0.54	22
Sundergarh	0.899	8	Baudh	0.536	23
Gajapati	0.914	7	Kendujhar	0.53	24
Koraput	0.943	6	Rayagada	0.443	25
Nabragapur	0.993	5	Nabarangapur	0.436	26
Rayagada	1.009	4	Koraput	0.431	27
Khandhamal	1.079	3	Gajapati	0.431	28
Nuapara	1.099	2	Kandhamal	0.389	29
Malkanigiri	1.107	1	Malkangiri	0.37	30

The least vulnerable districts to CIND in Orissa are Khurda, Puri, Jagatsingpur, Kendrapada and Bhadrak. These districts of Orissa have high capability to cope with climate induced extreme events because of less reliance on natural resources, less percentage of population belong to marginalized sections of the society, less prevalence of poverty and have wide range of capacity to adapt financially and institutionally. The district of Khurda topped the list because of less degree of poverty (59.17%), high percentage of urbanization (42.93%), having access to alternative sources of income, low dependency ratio (19.86), and have less percentage of population from marginalized

section. The coastal district of Puri is famous for its historic antiquities, religious sanctuaries, architectural grandeur, beautiful sea beaches and moderate climate, secured second position in the row having relatively more potential to deal with CIND than other districts. The district of Puri has less prevalence of poverty, less percentage of ST population, high literacy rate, larger percentage of population is engaged in the secondary sector and the income generated from tourism sector plays indirect role to make district economically sound than other districts to cope with natural disasters.

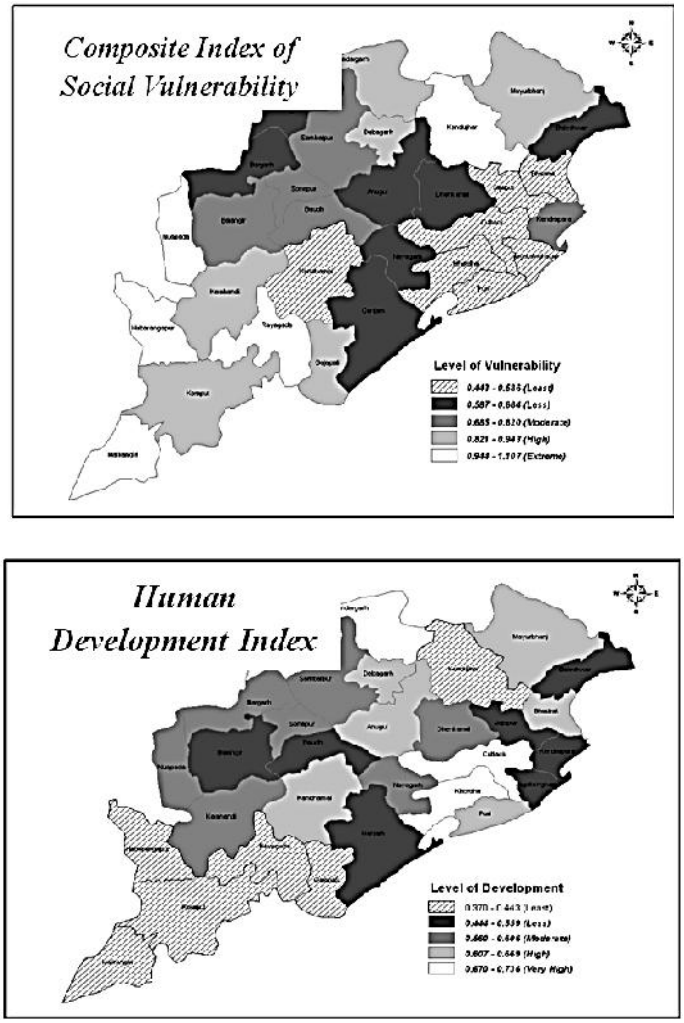

Fig. 2.

The district of Jagatsingpur rank 3rd in coping ability is because of low percentage

of SC and ST (22.23%), low level of poverty, high literacy rate and health condition in this district. The district of Kendrapa and Bhadarak rank 4th and 5th position, respectively in hierarchy in coping ability to CIND in Orissa. The coping ability of both the districts are quite high in ranking because of high level of urbanization, low percentage of ST population, low amount of poverty, diversified economic activity and access to good education and information technology. These coastal districts have high potential to absorb the climatic shocks and stresses in the whole state.

The least Vulnerable districts in Orissa to CIND

Table 6.

District	CISV-Score	Rank
Khurda	0.443	30
Puri	0.520	29
Jagatsinpur	0.525	28
Kendrapa	0.557	27
Bhadrak	0.564	26

Source: Human Development Report-2004.

DISCUSSION

The result of the research paper showed the possibility to determine the relative social vulnerability of a high complex socio-economic landscape of Odisha. The standard statistical techniques used in this research are of first of kind applied in a developing country context with challenges of non availability of relevant data. However there are numerous approaches available for construction of vulnerability index, but this method is step forward in our ability to map useful indices.

Table 7: Correlation with CISV and HDI

	CISV	HDI
CISV		
Pearson Correlation	1	-.635**
Sig (2-tailed)		.000
N	31	31
HDI		
Pearson Correlation	-.635**	1
Sig (2-tailed)	.000	
N	31	31

**. Correlation is significant at the 0.01 level.

Furthermore, these kinds of investigation only prioritize the mitigations and adaptation strategies of the state. The difficulty in validating the indices of social vulnerability strive the us to understand the limitation of the methodology of these kind of studies. Knowing the limitation, to understand the reliability and usefulness of CISV, the correlation between CISV and HDI are examined. The relation between CISV and HDI are found inverse i.e. the district having high human development index should have low social vulnerability i.e. coping ability should be high and vice versa. There is a moderate, negative association (- 0.635) between CISV and HDI (Table 7).

However, as a proof concept, the Human Development Index (HDI) and its level of social vulnerability (CISV) might yield some useful insights. The HDI measures well being taking only few socio-economic indicators and does not include various non conventional social indicators. There are several reasons for using CISV instead of HDI for measuring coping ability against climate induced natural disaster. First, one of the stated goals of the HDI is to achieve a stable indicator therefore HDI may mask much of the variability in Social Vulnerability that can be identified by the CISV. Second, CISV has a much stronger theoretical base in measuring both potential of society to cope with disaster and developmental aspects than HDI. The CISV tries to give different weight using multivariate technique (PCA) to indicators for the construction of better index. This is not to suggest that the CISV does not need further refinement, but it is a better and more interesting indicator than the HDI, particularly while developing composite index at micro-level study (district, block and villages).

CONCLUSION

The academia does not have consensus within their community about social vulnerability or its correlates. These correlates are largely derived from local case studies of climate induced natural disasters and community responses. There have been few attempts to develop larger theoretical or conceptual understandings about dynamic indicators of social vulnerability, however, it is needed to develop a robust and replicable set of indicators. The work on the Composite Index of Social Vulnerability demonstrates that it has a considerable potential of measuring sustainability, development, climate change impacts, disaster managements and any other kind of spatial changes. The CISV can assist local decision-makers in pinpointing those factors that threaten sustainability and stability of the districts (or community).

Using this index in conjunction with biophysical risk index can help in mitigating adverse effects or empower the manager of disaster management who can target the most vulnerable groups or districts. Whilst the index has important academic and policy applications, its development has also raised a number of potential directions for further research. The limitations of the study include non availability of secondary data over a period of time for all the indicators considered in this study and changing criteria adopted by concerned agency while providing data for specific indicator. Missing

values have been generated using interpolation and regression analysis is another limitation of the study. Results of the study should be viewed with appropriate regards to the limitations, however, it can be considered as the first robust and systematic assessment of relative levels of social vulnerability in Orissa. It is an index constructed on micro scale and a complimentary index to Human Development Index constructed by UNDP. There is a need to try and validate the index by applying the model (with appropriate data) to past historical hazards to explain why they did or did not translate into impacts (disasters). The researchers should try in developing robust indicators and indexes which can really capture the ground reality. As international agreements such as the UN Framework Convention on Climate Change incorporate the goals of sustainable development and human threats as key provisions, there will be a need for additional research on indicators for measurement and prediction. The CISV presents an effort towards meeting this need.

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